iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 14 **Issue:** I **Month of publication:** January 2026

DOI: https://doi.org/10.22214/ijraset.2026.76877

www.ijraset.com

Call: 08813907089 | E-mail ID: ijraset@gmail.com

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue I Jan 2026- Available at www.ijraset.com

A Study on Health Monitoring Machine Algorithm for Turbo-Fan Engine

Kshatriya Samir Singh
III Semester M. Tech, Gandhinagar Institute of Technology, Gandhinagar

Abstract: The increasing complexity and safety-critical nature of aircraft engines have made effective health monitoring and predictive maintenance essential in modern aviation systems. Turbofan engines operate under extreme conditions, where unexpected component degradation can lead to serious failures, high maintenance costs, and operational downtime. Traditional maintenance strategies, such as reactive and preventive maintenance, are no longer sufficient to handle these challenges efficiently. As a result, data-driven approaches based on machine learning and deep learning have gained significant attention in prognostics and health management (PHM) applications. This review focuses on health monitoring and remaining useful life (RUL) prediction of turbofan engines using advanced deep learning techniques. It examines how sensor data collected from aircraft engines can be utilized to detect degradation patterns and estimate future engine health. Particular emphasis is placed on hybrid deep learning models that combine feature extraction and temporal sequence learning, such as convolutional neural networks, autoencoders, and long short-term memory networks. The study also discusses publicly available benchmark datasets, especially the NASA C-MAPSS dataset, which is widely used for validating RUL prediction models. Key challenges such as data imbalance, noise, model interpretability, and real-time deployment are highlighted. Overall, this review demonstrates that deep learning-based prognostic models play a crucial role in improving prediction accuracy, enhancing aviation safety, and enabling reliable condition-based maintenance strategies for turbofan engines.
Keywords: Turbofan Engine, Health Monitoring, Prognostics and Health Management (PHM), Remaining Useful Life (RUL) Prediction, Predictive Maintenance, Deep Learning, Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), Autoencoders, Attention Mechanism, Time-Series Analysis, NASA C-MAPSS Dataset, Aviation Safety, Condition-Based Maintenance.

I. INTRODUCTION

The rapid growth of the aviation industry has significantly increased the demand for safe, reliable, and cost-effective aircraft operations. Turbofan engines, being one of the most critical components of modern aircraft, operate under extreme mechanical and thermal conditions. Over time, continuous operation leads to gradual degradation of engine components, which can result in reduced performance, unexpected failures, and increased maintenance costs. Ensuring the health and reliability of turbofan engines is therefore a major concern for airlines, manufacturers, and regulatory authorities.

Traditionally, aircraft engine maintenance has relied on reactive or preventive strategies. Reactive maintenance addresses failures only after they occur, often leading to costly downtime and safety risks. Preventive maintenance, on the other hand, schedules maintenance activities at fixed intervals, which may result in unnecessary part replacements and increased operational expenses. These limitations have motivated the shift toward condition-based maintenance and predictive maintenance strategies, where maintenance decisions are based on the actual health condition of the engine.

Prognostics and Health Management (PHM) plays a vital role in this transformation by enabling early fault detection, degradation assessment, and prediction of the Remaining Useful Life (RUL) of engine components. With the availability of advanced sensors and onboard monitoring systems, large volumes of time-series data can be collected during engine operation. Analysing this data effectively is essential for understanding degradation behaviour and predicting future engine health.

In recent years, data-driven approaches based on machine learning and deep learning have shown strong potential for turbofan engine health monitoring. Deep learning models such as Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) networks, and hybrid architectures are particularly well-suited for handling multivariate time-series sensor data. These models can automatically learn complex patterns and temporal dependencies associated with engine degradation. However, challenges such as data noise, class imbalance, model complexity, and interpretability remain open research issues.

This review explores recent advancements in deep learning-based health monitoring and RUL prediction for turbofan engines. It examines commonly used datasets, model architectures, evaluation techniques, and existing challenges, highlighting future research directions for building reliable and efficient predictive maintenance systems in aviation.

II. LITERATURE REVIEW

This section presents a comprehensive review of existing research related to turbofan engine health monitoring, prognostics and health management (PHM), and remaining useful life (RUL) prediction using machine learning and deep learning techniques. The reviewed studies primarily focus on leveraging multivariate sensor data to model engine degradation behavior, improve prediction accuracy, and support predictive maintenance strategies. In addition, the literature addresses key challenges such as handling high-dimensional time-series data, capturing long-term degradation patterns, ensuring model robustness under varying operating conditions, and improving interpretability for practical maintenance decision-making.

A. CNN-Based RUL Prediction Using Multivariate Sensor Data

In this study, researchers proposed a deep Convolutional Neural Network (CNN)–based regression model for predicting the Remaining Useful Life (RUL) of turbofan engines using multivariate time-series sensor data from the NASA C-MAPSS dataset. The model utilized convolution and pooling layers to automatically extract degradation patterns from sensor signals across different temporal scales. By learning spatial correlations among sensor readings, the CNN was able to capture local degradation features that traditional machine learning models often fail to detect. The performance of the model was evaluated using Root Mean Square Error (RMSE) and NASA's scoring function on FD001 and FD003 datasets. Although the CNN-based approach showed improvement over traditional regression techniques, it struggled to capture long-term temporal dependencies inherent in engine degradation data. This limitation reduced its effectiveness in modelling progressive wear over long operational cycles. The authors concluded that while CNNs are effective for feature extraction, combining them with temporal models such as LSTM could further enhance prediction accuracy. This work laid the foundation for hybrid deep learning architectures in turbofan engine prognostics.

B. MODBNE: Multi-Objective Deep Belief Network Ensemble

This paper introduced a Multi-Objective Deep Belief Network Ensemble (MODBNE) for RUL prediction of turbofan engines. The proposed approach evolved multiple Deep Belief Networks (DBNs) while optimizing accuracy and diversity simultaneously. A differential evolution algorithm was employed to determine optimal ensemble weights. The model was evaluated using FD001 and FD003 datasets from C-MAPSS, achieving lower RMSE values compared to individual DBN models. The ensemble strategy improved robustness and reduced prediction variance. However, DBNs require extensive tuning and are computationally expensive, limiting real-time applicability. Additionally, the model lacked interpretability, making it difficult for maintenance engineers to understand degradation causes. Despite these limitations, the study demonstrated the effectiveness of ensemble learning in improving RUL prediction accuracy. The authors suggested future work involving GPU acceleration and extending the framework to health state classification. This research contributed significantly to ensemble-based prognostics but highlighted the need for explainable and efficient architectures.

C. LSTM-Based Sequence Learning for RUL Estimation

This research proposed a deep learning framework using Long Short-Term Memory (LSTM) networks for predicting the RUL of turbofan engines. LSTMs are well-suited for time-series data due to their ability to capture long-term dependencies. The authors applied the model to C-MAPSS FD001 and FD003 datasets and evaluated performance using RMSE and scoring metrics. The LSTM-based model demonstrated superior performance compared to traditional neural networks and regression models. However, training LSTMs required extensive computational resources, and the model suffered from overfitting when trained on limited datasets. Additionally, the lack of feature-level interpretability made it difficult to justify predictions. The authors concluded that while LSTM models effectively learn degradation trends, integrating preprocessing techniques and feature extraction mechanisms could further enhance performance. This work established LSTM as a dominant model for turbofan RUL prediction.

D. Deep RNN with Multiple LSTM Layers

This study explored the use of a deep Recurrent Neural Network (RNN) with multiple LSTM layers for RUL estimation of aircraft engines. The model leveraged stacked LSTM layers to capture complex temporal relationships within sensor data. Evaluated on the FD001 dataset, the model achieved competitive RMSE scores. However, deeper architectures increased training time and memory consumption. The authors emphasized that deeper networks are more prone to vanishing gradients and require careful hyperparameter tuning. Despite strong performance, the approach lacked robustness across varying operational conditions. The study highlighted the importance of balancing model depth and computational efficiency. This work contributed to understanding the trade-offs involved in deep sequential models for prognostics.

E. Hybrid LSTM with Sensor Fusion

In this research, a hybrid deep LSTM framework was proposed for machinery prognostics by integrating sensor fusion techniques. Multiple sensor streams were combined at the data level to improve RUL prediction accuracy. The model was trained directly on raw sensor data, reducing dependency on manual feature engineering. The results showed improved accuracy compared to single-sensor models. However, the fusion of high-dimensional data increased computational complexity. The study demonstrated that sensor fusion enhances degradation pattern recognition, making it valuable for complex turbofan systems. This work reinforced the importance of multivariate analysis in PHM.

F. Ensemble RNN-Based Stacking Framework for Turbofan RUL Prediction

This study proposed an ensemble-based recurrent neural network (RNN) framework for predicting the Remaining Useful Life (RUL) of turbofan engines, with a specific focus on improving robustness and generalization across varying operating conditions. The authors combined multiple sequential models, including Long Short-Term Memory (LSTM), Gated Recurrent Units (GRU), and standard RNN architectures, using a stacking ensemble strategy. Each base learner was trained independently on multivariate sensor data obtained from the NASA C-MAPSS dataset, particularly FD001 and FD003 subsets. The predictions generated by these base models were then combined using a meta-learner, which learned optimal weights for final RUL estimation.

The motivation behind this approach was to reduce prediction variance and mitigate the weaknesses of individual models. Experimental results demonstrated that the ensemble model achieved lower RMSE values compared to single LSTM or GRU models, indicating improved prediction accuracy and stability. The study highlighted that different RNN architectures capture degradation patterns differently, and stacking enables the model to exploit complementary learning behaviors.

However, the approach significantly increased computational complexity and training time, making real-time deployment challenging. Additionally, the ensemble framework lacked interpretability, as it did not provide insights into which sensors or temporal segments contributed most to predictions. Despite these limitations, the research demonstrated the effectiveness of ensemble learning for turbofan engine prognostics and reinforced the importance of model diversity in RUL estimation. The study serves as an important reference for hybrid and ensemble-based predictive maintenance systems.

G. Bidirectional LSTM Autoencoder for Degradation Representation Learning

This paper introduced a bidirectional Long Short-Term Memory autoencoder (BiLSTM-AE) framework for learning degradation representations and estimating the Remaining Useful Life of turbofan engines. The authors aimed to improve feature learning by capturing both forward and backward temporal dependencies within multivariate sensor sequences. The autoencoder structure compressed high-dimensional sensor data into low-dimensional latent representations that preserved degradation-related information. The model was evaluated using the NASA C-MAPSS FD001 dataset, where sensor signals exhibit progressive degradation patterns. The bidirectional nature of the LSTM enabled the model to consider historical as well as future context during training, resulting in more stable representations. These latent features were then used for RUL regression. The results showed improved RMSE scores compared to traditional autoencoders and unidirectional LSTM models.

Despite strong performance, the model required extensive hyperparameter tuning and high computational resources. Additionally, bidirectional architectures are not directly suitable for online prediction scenarios, as future data points are unavailable during real-time inference. The lack of explainability further limited practical adoption. Nonetheless, this work contributed significantly to representation learning in prognostics and highlighted the value of autoencoder-based architectures in turbofan health monitoring.

H. Attention-Based LSTM Network for Interpretable RUL Prediction

This research proposed an attention-enhanced Long Short-Term Memory (LSTM) model to improve both accuracy and interpretability of turbofan engine RUL prediction. The key objective was to address the black-box nature of deep learning models by enabling the network to identify critical time steps contributing to degradation. The attention mechanism assigned dynamic weights to different temporal segments of sensor data, allowing the model to focus on the most informative degradation phases.

The approach was validated using NASA C-MAPSS FD001 and FD004 datasets. Experimental results demonstrated that the attention-based LSTM achieved lower RMSE and better scoring metrics than standard LSTM models. Additionally, attention weights provided intuitive insights into degradation progression, making the model more transparent for maintenance engineers.

However, the attention mechanism increased model complexity and training time. Interpretation of attention weights also required domain expertise to avoid misinterpretation. Despite these challenges, the study represented a major step toward explainable deep learning for aircraft engine prognostics. It emphasized that accuracy and interpretability can coexist in RUL prediction models.

I. Time-Series Chain Graph Model for Turbofan Degradation Analysis

This study introduced a Time-Series Chain Graph (TSCG) framework to model dependencies between degradation factors and sensor observations in turbofan engines. Unlike purely data-driven models, the proposed probabilistic approach explicitly represented causal relationships among variables over time. The model was tested using the C-MAPSS dataset and demonstrated improved degradation detection capabilities.

The TSCG approach offered better interpretability than deep learning models, as it allowed engineers to trace degradation causes. However, the method required extensive domain knowledge and was computationally expensive. The study highlighted the trade-off between interpretability and scalability in turbofan prognostics.

J. Semi-Supervised Autoencoder for Anomaly Detection in Turbofan Engines

This research focused on anomaly detection rather than direct RUL prediction. A semi-supervised autoencoder was trained using healthy engine data to learn normal operational behavior. Deviations from reconstruction patterns were used to detect early anomalies. Bayesian optimization was applied to tune hyperparameters.

The model successfully identified abnormal degradation trends in C-MAPSS data. However, it did not provide explicit RUL estimates. The study emphasized early fault detection as a critical component of predictive maintenance pipelines.

K. LSTM Autoencoder-Based Health Index Construction

This paper proposed an LSTM autoencoder framework to construct a Health Index for aircraft engines. The Health Index provided a continuous representation of engine degradation over time. The approach enabled early detection of abnormal behaviour and supported maintenance decision-making. Despite promising results, threshold selection remained a challenge. The study highlighted the importance of health indicators in bridging anomaly detection and RUL prediction.

L. Hybrid Hidden Markov Model and LSTM Framework

This study combined Hidden Markov Models (HMMs) with LSTM networks to leverage interpretability and temporal modelling. HMMs modelled discrete health states, while LSTMs captured degradation dynamics. The hybrid approach achieved balanced performance but increased system complexity.

M. DAE–LSTMQR–KDE Framework for Predictive Maintenance of Turbofan Engines

This study proposed an advanced predictive maintenance framework that integrates Deep Autoencoders (DAE), Long Short-Term Memory networks (LSTM), Quantile Regression (QR), and Kernel Density Estimation (KDE) to improve Remaining Useful Life (RUL) prediction for turbofan engines. The primary objective of this work was to enhance prediction accuracy while also quantifying uncertainty in RUL estimation, which is critical for risk-aware maintenance decision-making. The framework was evaluated using the NASA C-MAPSS dataset, where high-dimensional sensor data and nonlinear degradation behaviour pose significant challenges. The deep autoencoder component was employed to reduce sensor dimensionality and extract meaningful latent degradation features from multivariate time-series data. These extracted features were then fed into an LSTM network to capture long-term temporal dependencies associated with engine degradation. Unlike traditional regression approaches that produce single-point predictions, quantile regression was used to estimate multiple quantiles of the RUL distribution, providing interval-based predictions. Kernel Density Estimation further refined the uncertainty representation by modelling probability distributions over predicted RUL values. Experimental results demonstrated improved prediction accuracy compared to standard LSTM-based models, particularly in scenarios with noisy sensor data. The uncertainty-aware predictions enabled more flexible and safer maintenance planning. However, the framework introduced significant computational complexity and required careful tuning of multiple model components. Additionally, real-time deployment was not evaluated. Despite these limitations, this work made a valuable contribution by emphasizing uncertainty estimation in turbofan prognostics, an aspect often overlooked in existing research.

N. PCA-Assisted LSTM Model for Efficient Turbofan RUL Prediction

This paper presented a hybrid approach that combines Principal Component Analysis (PCA) with Long Short-Term Memory (LSTM) networks to improve computational efficiency in turbofan engine RUL prediction. The motivation behind this work was to address the high dimensionality and redundancy present in multivariate sensor data collected from aircraft engines. High-dimensional inputs often increase training time and risk overfitting, especially in deep learning models.

The proposed methodology first applied PCA to transform the original sensor data into a lower-dimensional feature space while preserving the majority of variance related to degradation behaviour. These reduced features were then used as input to an LSTM network for time-series modelling and RUL estimation. The model was evaluated using NASA C-MAPSS datasets, and performance was assessed using RMSE and standard prognostics scoring functions.

Results showed that the PCA-LSTM model significantly reduced training time and memory requirements compared to baseline LSTM models trained on raw sensor data. Although there was a slight reduction in prediction accuracy, the performance trade-off was considered acceptable given the computational gains. However, the PCA transformation reduced model interpretability, as principal components do not have direct physical meaning. Additionally, the model's performance depended heavily on the number of retained components.

This study highlighted an important trade-off between efficiency and accuracy and demonstrated that dimensionality reduction techniques can play a crucial role in scalable turbofan prognostics.

O. Convolutional Autoencoder with Attention-Based LSTM (CAELSTM) for Turbofan Prognostics

This recent work proposed a state-of-the-art deep learning architecture known as CAELSTM, which integrates Convolutional Autoencoders (CAE) with an Attention-based Long Short-Term Memory (LSTM) network for turbofan engine Remaining Useful Life prediction. The objective of this approach was to combine effective feature extraction, temporal modeling, and interpretability within a single unified framework. The model was evaluated extensively using NASA C-MAPSS FD001 and FD003 datasets.

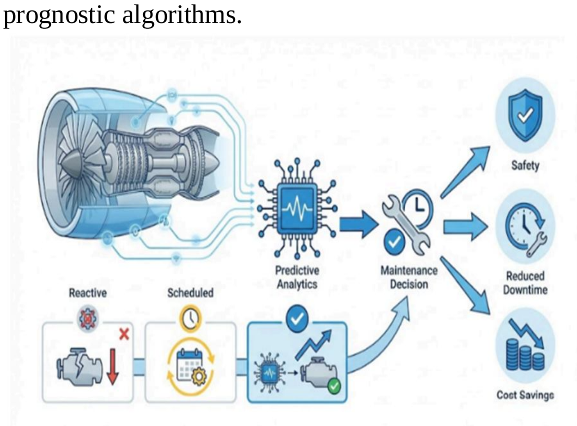
The convolutional autoencoder component was used to automatically extract robust degradation features from high-dimensional sensor data by learning spatial correlations among sensors. These features were then passed to an attention-enhanced LSTM network that captured long-term temporal dependencies while assigning importance weights to critical time steps. The attention mechanism enabled the model to focus on significant degradation phases, improving both accuracy and transparency.

Experimental results showed that CAELSTM achieved state-of-the-art RMSE and scoring metrics compared to conventional LSTM and CNN-based models. The attention weights provided valuable insights into degradation progression, improving model interpretability for maintenance engineers. However, the model required substantial computational resources and was primarily evaluated in an offline setting. Despite these challenges, this work represents a major advancement in turbofan engine prognostics by successfully integrating accuracy, robustness, and interpretability, making it a strong foundation for future research in predictive maintenance systems.

III. METHODOLOGY

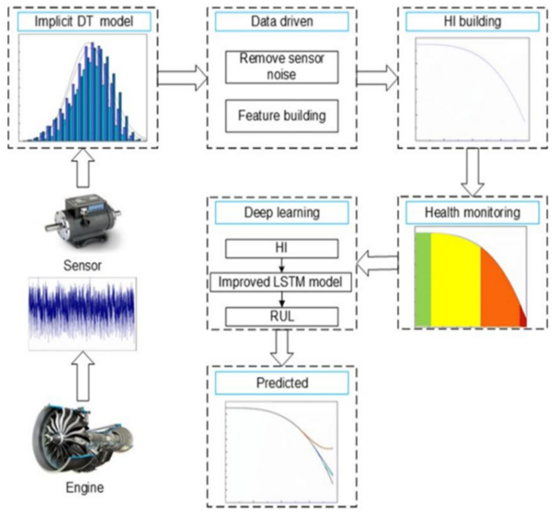
The methodology discussed in this review focuses on data-driven approaches for health monitoring and Remaining Useful Life (RUL) prediction of turbofan engines. Rather than proposing a single implementation, this section outlines the general methodological pipeline commonly adopted in recent research studies, highlighting best practices, model architectures, and evaluation strategies used in turbofan prognostics.

The process begins with data acquisition, where engine operational data is collected through onboard sensors installed at various engine components. These sensors continuously monitor parameters such as temperature, pressure, vibration, fuel flow, and rotational speed. Most reviewed studies utilize the NASA Prognostics Data Repository (C-MAPSS), which simulates realistic turbofan engine degradation under different operating and fault conditions. The dataset provides multivariate time-series data that serves as a benchmark for evaluating prognostic algorithms.



Following data acquisition, data preprocessing is performed to enhance data quality. This step includes normalization of sensor values, removal of non-informative or constant sensors, handling missing values, and segmentation of time-series data into meaningful operational cycles. Since engine degradation evolves gradually, preprocessing plays a critical role in preserving temporal patterns essential for accurate RUL prediction.

The next stage involves feature extraction and representation learning. Traditional approaches rely on handcrafted statistical features, while modern studies increasingly adopt deep learning-based feature learning techniques. Models such as Convolutional Neural Networks (CNNs) and autoencoders are used to automatically extract degradation-related features from high-dimensional sensor data, reducing dependency on manual feature engineering.



For temporal modeling, sequential learning algorithms such as Long Short-Term Memory (LSTM) networks and Gated Recurrent Units (GRUs) are widely employed due to their ability to capture long-term dependencies in time-series data. Hybrid architectures combining feature extractors with sequence models, including attention mechanisms, have shown improved performance by focusing on critical degradation phases.

Model performance is evaluated using metrics such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and domain-specific scoring functions. Cross-validation and testing across multiple operating conditions ensure robustness and generalization. Overall, the reviewed methodology demonstrates a systematic approach to turbofan engine prognostics, emphasizing accuracy, robustness, and practical applicability in predictive maintenance systems.

IV. CONCLUSION

The increasing operational demands and safety requirements of the aviation industry have made effective health monitoring and predictive maintenance of turbofan engines a critical research area. This review examined recent advancements in data-driven approaches for engine health assessment and Remaining Useful Life (RUL) prediction, with a particular focus on machine learning and deep learning techniques. The surveyed literature demonstrates that traditional maintenance strategies are gradually being replaced by predictive models capable of analyzing multivariate sensor data to identify degradation patterns and forecast future engine behavior. Deep learning models, especially Long Short-Term Memory networks, convolutional architectures, and hybrid frameworks, have shown strong performance in capturing complex temporal relationships within sensor data. The use of publicly available benchmark datasets such as NASA's C-MAPSS has enabled consistent evaluation and comparison of different prognostic methodologies. However, several challenges remain, including high computational complexity, limited interpretability of deep models, and difficulties in real-time deployment under varying operational conditions. This review highlights the need for more robust, explainable, and scalable predictive maintenance solutions that integrate domain knowledge with data-driven techniques. Future research should focus on improving model transparency, incorporating uncertainty estimation, and optimizing computational efficiency to support real-world aviation applications. Overall, advanced prognostic models hold significant potential for enhancing aircraft safety, reducing maintenance costs, and enabling reliable condition-based maintenance strategies for turbofan engines.

REFERENCES

[1] S. M. Elsherif, B. Hafiz, M. A. Makhlouf, and O. Farouk, "A deep learning-based prognostic approach for predicting turbofan engine degradation and remaining useful life," Scientific Reports, vol. 15, no. 1, pp. 1–18, 2025.

[2] O. Asif, M. A. Khan, and A. Raza, "A deep learning model for remaining useful life estimation of turbofan engines," IEEE Access, vol. 10, pp. 102345–102357, 2022.

[3] C. Peng, Y. Liu, and Z. Zhang, "Turbofan engine health assessment based on spatial–temporal similarity," Mathematics, vol. 11, no. 3, pp. 1–20, 2023.

[4] M. Soualhi, G. Medjaher, and N. Zerhouni, "Explainable remaining useful life estimation of turbofan engines," Engineering Applications of Artificial Intelligence, vol. 125, pp. 1–14, 2024.

[5] T. Szrama, P. Czech, and J. Łazarz, "Turbofan engine health status prediction with artificial neural networks," Aviation, vol. 28, no. 2, pp. 85–97, 2024.

[6] A. da Silva, J. B. C. Engler, and R. R. Filho, "A machine learning approach to forecasting turbofan engine removal via EGT trend," AIAA Journal, vol. 60, no. 9, pp. 5234–5246, 2022.

[7] M. L. Baptista, S. Sankararaman, and K. Goebel, "1D-DGAN-PHM: A denoising GAN for prognostics and health management with application to turbofan engines," Applied Soft Computing, vol. 118, pp. 1–12, 2022

[8] Z. Hrncir and C. Hickenbottom, "A practical example of applying machine learning to a real turbofan engine issue," PHM Society Conference Proceedings, vol. 15, no. 1, pp. 1–9, 2023.

[9] A. Dal Pozzolo, O. Caelen, Y.-A. Le Borgne, and G. Bontempi, "Learned lessons in credit card fraud detection from a practitioner perspective," Expert Systems with Applications, vol. 41, no. 10, pp. 4915–4928, 2014.

[10] J. Chen, Y. Li, and X. Wang, "Deep learning techniques for remaining useful life prediction: A review," Reliability Engineering & System Safety, vol. 210, pp. 1–15, 2021.

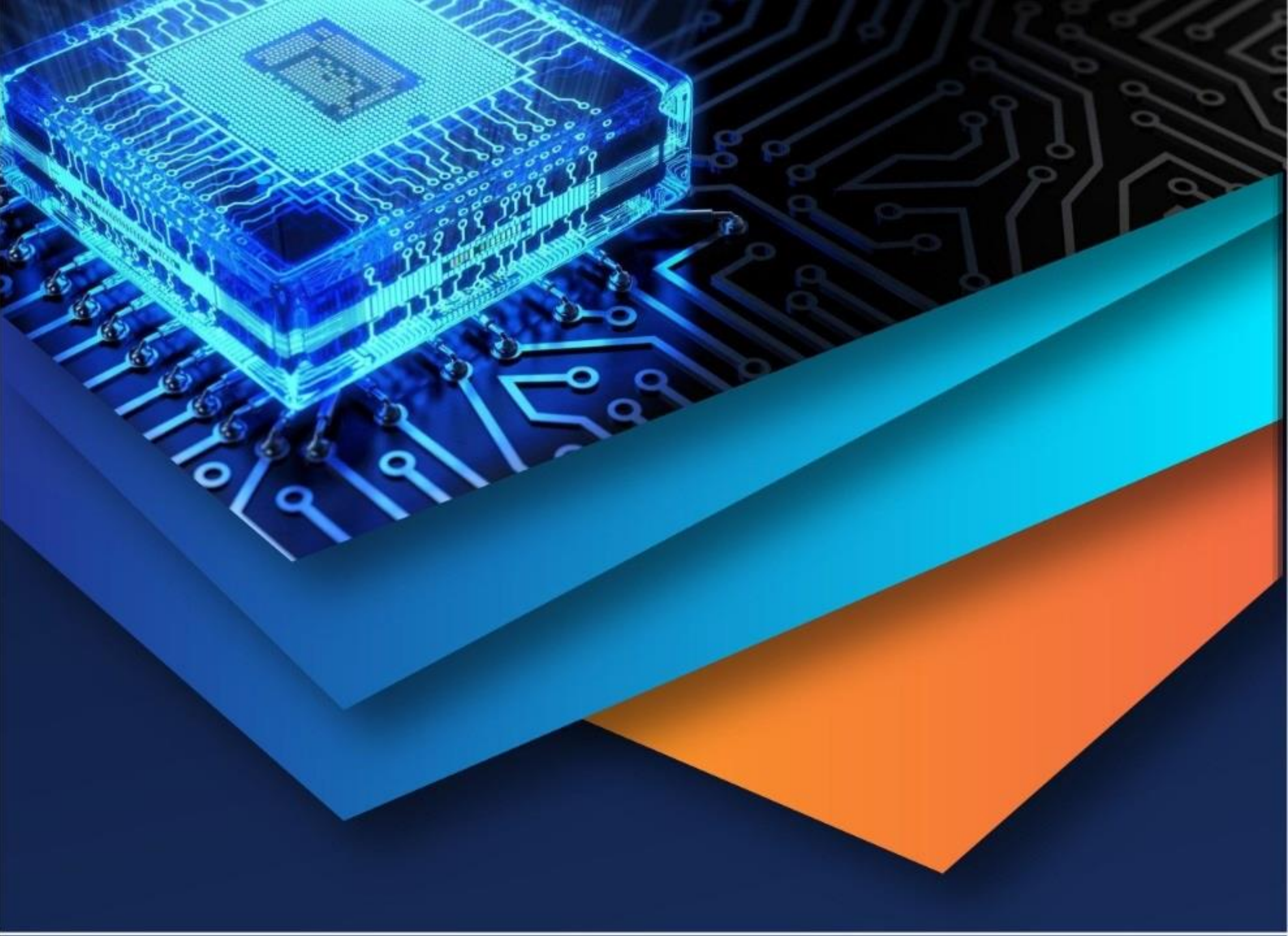
[11] K. Goebel, A. Saxena, and N. Eklund, "Prognostics and health management of aerospace systems," Journal of Aerospace Engineering, vol. 23, no. 4, pp. 251–26

[12] E. Ramasso and C. Saxena, "Performance benchmarking and analysis of prognostic methods for turbofan engines," International Journal of Prognostics and Health Management, vol. 5, no. 1, pp. 1–15, 2014.

[13] S. Javed, T. Gouriveau, and N. Zerhouni, "A hybrid approach for prognostics of industrial systems," Mechanical Systems and Signal Processing, vol. 72–73, pp. 64–80, 2016.

[14] A. Saxena and K. Goebel, "Turbofan engine degradation simulation data set," NASA Ames Prognostics Data Repository, 2008.

[15] Y. Lei, N. Li, L. Guo, N. Li, T. Yan, and J. Lin, "Machinery health prognostics: A systematic review from data acquisition to RUL prediction," Mechanical Systems and Signal Processing, vol. 104, pp. 799–834, 2018.



10.22214/IJRASET

INDEX COPERNICUS

45.98

IMPACT FACTOR: 7.129

TOGETHER WE REACH THE GOAL

IMPACT FACTOR: 7.429

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Call : 08813907089 (24*7 Support on Whatsapp)